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Online intention learning for human-robot interaction by scene observation

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Abstract—**Intention recognition plays a key role in the cooperation among the humans. An intention describes an action or sequence of actions to be performed for achieving the intended purpose. The cooperating humans learn each others intentions while cooperation. In this paper we propose three ways how a robot can learn the intention of the cooperating human. In the first case, the robot learns the human intention by mapping the known human intention given in terms of scene information to the observed action sequence. The actions are already known to the robot. In the second case, the robot is only given the human actions but the robot estimates the human intention in terms of the changes that occur in the scene due to the human actions. The robot learns the human intention by mapping the observed action sequence to the human intention. The human intention is estimated from the scene information. In the third case, only the scene information is used in order to learn the human intention mapping. The scene information is used to infer the human actions as well as the human intention.**

I. Introduction

Human-robot interaction (HRI) is one of the emerging areas of robotic research. There may be many fields of life where HRI is useful as the robot assists the human. For a robot in collaboration with human, it is important to be able to identify the intention of the interacting person. A human has his intentions depending on the scenario, the goal, and the tasks that he is to perform in the current situation. A human has different intentions at different places. It is difficult to model all the possible human intentions as the total number of human intentions can be huge. Therefore learning the human intentions from his actions and the scene information can help the robots to cooperate more intuitively.

In literature, there is no solution for online intention learning in the area of human-robot collaboration by intention recognition. There exists Hidden Markov Model (HMM) based gestures understanding solutions [4] that require the Baum-Welch algorithm to train the Markov models. They deal with the recognition of actions and gestures but not with the intention of a human. The available approaches for action recognition consider the image-processing as a core issue. There exist many human action recognition methods based on feature tracking [2, 20], intensity or gradient, and silhouette [11]. The human actions can be recognized based on the pose primitives [5]. The 2D human actions are recognized in the approach proposed in [6]. Similarly the approach in [9] uses local motion appearance features to recognize the human action. The action recognition using HMM corresponds to different phases or key poses of the human while perfuming an action. These key poses are considered as the hidden states of HMM [15]. The presented approach has vital differences from gesture and action recognition. The approach does not focus on single action rather an action sequence concerning the human intention. Further the core issue is not image-processing concerning modeling of different human poses. It models the action sequence and environment information concerning the human intention. Another difference corresponds to the fact that activity / gesture / action can only be recognized if the concerning action / gesture / activity is completely performed [16]. A multitude of research work already exists in the field of Programming by Demonstration (PbD) in the direction of intention recognition. But the research work does not directly relate to the human-robot collaboration; because it commands the robot an action based on the demonstrated program [3]. The solutions present in the area of PbD use reinforcement learning [14], neural networks [1], HMM [8] and Radial Basis Function [19]. In the proposed approach presented in this paper, a mapping is performed between the observations (action and / or scene sequences) and the human intentions. Once the mapping is performed then it can be used to understand the human intention for intuitive collaboration. We formulate the problem of intention learning as finding the mapping without considering the hidden states as considered in HMM. There exists a hidden state concerning each observation in HMM. In the presented approach, the whole action sequence is modeled to represent a human intention, i.e., hidden state. In the literature, there exist multiple approaches for intention recognition. The approach proposed in [10] uses Dynamic Bayesian Network, in [13] uses Hybrid Dynamic Bayesian Network. The approach proposed in [7, 17, 18] use Ontology, Graph and Utility based intention recognition. The approach [16] uses a novel formulation of HMM to recognize the human intention. The intention recognition approach introduced in [12] uses probabilistic Finite State Machines (*FSM*). The described approaches recognize the human intention if the human intentions are already known and modeled. In case if the new intention is to be recognized then that has to be modeled explicitly by the human. The proposed approach describes how a new human intention can be added without the explicit modeling by the human. The intention of a human

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corresponds to what the human intends to do. There can be multiple ways of recognizing the human intention, e.g., ask the human, guess the intention by the daily routine, estimate the intention by the concerning action sequence, etc. In the proposed approach, the human intention is modeled by the concerning action sequence.

In this paper, different intention learning methods along with the experiments are discussed. The input to these methods varies but the output of all the methods are the mapped human intentions. The input to the methods involves the scene information, i.e., the objects present in the scene, the human actions, and / or the learning parameters. The *learning parameters* are the features which are specific to the given scene and enable to infer the scene changes. The *scene change* at a human-robot workplace corresponds to the modifications that can occur in the scene by the human actions. For example, if we consider the scene containing different number of objects then the distance among the objects, the number of objects, the types of objects, and the arrangements of the objects can be used as learning parameters. Learning parameters are different for different scenes depending on the nature of the scene. For example a mechanic working in a garage has different tools and objects around him along with the different intentions as compared to the craftsman working at his workplace. Therefore it is necessary to know the learning parameters, prior to learn the new intention.

The remainder of this paper is organized as follows: In the Section II three intention learning cases are introduced and discussed in detail. In Section III experimental results of the three intention learning cases are presented. We conclude in Section IV with remarks on the intention learning cases.

II. Intention Learning

The three different cases of mapping between the human intention and the observations (action and / or scene sequences) are discussed. The mappings differ from each other based on the given information: objects in the scene, human actions, the scene changes occurred due to the human actions, and the human intentions in terms of the scene information. This given information is used as input for the learning and recognition system. Generally, the input can not be specified as the input depends on the problem at hand. The mapping performed between the human intention and the observation sequence is described formally.

The intention $i_j \in I$, $j = 1,\ldots,p$ $I = \{i_1, i_2, i_3, \ldots, i_p\}$ corresponds to the scene information concerning the human intention. The *observation sequence* $o_k \in O$, $k = 1,\ldots,q$ $O = \{o_1, o_2, o_3, \ldots, o_q\}$ consists of the human actions and / or the scene changes occurred due to the human action. M is the mapping from the observed sequence $o_k \in O$ to the concerning intention $i_j \in I$, *i.e.*, $M(O) \rightarrow I$.

In the Case 1, the human actions, scene changes, objects in the scene, and different possible human intentions i_j, $j = 1,\ldots,p$ in terms of the scene information relating to the human-robot workspace are given. The human intention is learned by mapping the observed sequence o_k and the given intention i_j, i.e., $M(o_k) = i_j$. The observed sequence o_k corresponds to the human actions and / or scene changes. The intention is recognized from the scene information. The recognition is performed by the analysis of the already known information concerning the intention $i_j \in I$ and the information obtained from the current observation. In the Case 2, the given information consists of the human actions, the objects in the scene and the learning parameters. The output of the method is the mapping between the observed sequence o_k and the newly learned scene information (intention) $i_j \in I$. The scene information is produced by the changes occurred in the scene due to the performed human action sequence. The new intention $i_j \in I$ (scene information) is understood using the learning parameters. In the Case 3, the given information includes the objects present in the scene and the learning parameters and the output is the mapping between the observed sequence o_k and new intention $i_j \in I$ in terms of the scene information. The observed sequence o_k only consists of the scene changes occurred due to the human actions. In the Case 3, the mapping is performed between the sequence o_k (scene changes) and the last scene change that is considered as the human intention, i.e., $i_j \in I$. The scene changes except the last change are considered as the steps that may lead to a specific human intention described by the last scene change. The inference of the scene changes is performed using the learning parameters. While teaching the robot the intention, the teacher may repeat auxiliary tasks. It means a set of individual actions may be repeated while conveying the robot the human intentions, e.g., in case of pilling the boxes, the pickup and place actions are performed repeatedly and also the reduction of boxes in numbers in 2D is observed repeatedly. In order to get one unique set of concerned actions sequence and scene observation, all the possible combinations of actions (observed while teaching) are formed such that they have the length equal to the number of observed actions. Then for each combination it is checked how many times that combination occurs in the observed action sequence. The combination occurring maximum number of times is selected. This kind of combination searching is not performed in the Case 2 and the Case 3.

A. State Machine Construction

A *FSM* is built from the intention $i_j \in I$, $j = 1,\ldots,p$ and observed sequence $o_k \in O$, $k = 1,\ldots,q$ that may comprise either the performed human actions or the observed scene changes or both of them. At each scene change, occurred due to the human action a state S_i of a *FSM* is created. The scene change does not strictly correspond to a single event but can represent a single event. Therefore a state corresponds to an observation that may comprise one or more than one events occurring at the same time, e.g., a state may represent pileup operation of boxes that represents human action of placing the box and reduction of boxes in number, observable in 2D. The number of states in a constructed *FSM* is equal to the number of scene changes occurred due to the human actions. A *FSM* consisting of a tuple $\langle Q, \sum, q_0, F, \delta \rangle$ is described.

$$FSM = < Q, \Sigma, q_o, F, \delta >$$
$$Q = \{S_1, S_2, S_3, ..., S_n\}$$
$$\Sigma = \{a_1, a_2, a_3, ..., a_m\}$$
$$\forall S_i \in Q \wedge \forall a_x \in \Sigma \textit{ it holds that } \sum_{x=1}^{m} p(a_x \mid S_i) = 1$$
$$\forall S_i : \exists a_k \in \Sigma : \underset{j=1, j \neq k}{\overset{m}{\forall}} a_j \textit{ it holds that } \left[p(a_k \mid S_i) > p(a_j \mid S_i) \right]$$
$$\delta : Q \text{ x } \Sigma \rightarrow Q$$
$$\delta(S_i, a_j) = S_i \textit{ and } \delta(S_i, a_k) = S_{i+1} \quad i = 1, ..., n$$
$$q_0 = S_1$$
$$F = \{S_n\}$$

A *FSM* consists of a set Q of n states S_i, $i = 1,..,n$. Each state S_i of the *FSM* has a set $\sum$ of m transitions a_x, $x = 1,..,m$. The $m\text{-}1$ transitions a_j, i.e., $\underset{j=1, j \neq k}{\overset{m}{\forall}} a_j$ lead to the same state and only one transition a_k, i.e., $\exists a_k \in \Sigma \wedge k \neq j$ leads to the next immediate state, i.e., $\delta(S_i, a_k) = S_{i+1}$.

The transitions $\sum$ of a state may represent the possible human actions and / or the scene changes, occurred due to the human actions. The probability $P(a_j \mid S_i)$ of each transition represented as a_j for a state S_i is low and leads to the same state S_i, i.e. $\delta(S_i, a_j) = S_i$.

The transitions $a_j \;\; j \neq k \wedge j = 1,...,m$ concerning the state S_i, represent the human actions or the scene changes that were not observed at the time of creation of state S_i. The transition a_k represents the human action or the scene change that was observed during the construction of state S_i of the *FSM*. The probability $P(a_k \mid S_i)$ of human action or the scene change represented by a_k is the highest for the state S_i, i.e.,

$$S_i : \exists a_k \in \Sigma : \underset{j=1, j \neq k}{\overset{m}{\forall}} a_j \textit{ it holds that } \left[p(a_k \mid S_i) > p(a_j \mid S_i) \right]$$

The transition a_k leads to the next immediate state, i.e., $\delta(S_i, a_k) = S_{i+1}$. The transition probabilities concerning a state of a *FSM* adds up to 1, i.e.,

$$\forall S_i \in Q \wedge \forall a_x \in \Sigma \textit{ it holds that } \sum_{x=1}^{m} p(a_x \mid S_i) = 1$$

The end state of a *FSM* contains the information about the already known intention or the apprehensible scene information using the learning parameters. This is the final configuration of the objects due to the human actions.

These transition probabilities $P(a_x \mid S_i)$ are used to update the weights of the *FSM* if any of the apprehensible events is observed. The probability value of an event represents the significance of that event for the current state of a *FSM*.

The probability value of an event directly influences the weight of a *FSM*. The weight of each *FSM* represents the probability of the intention, represented by that *FSM* [12]. A general *FSM* is shown in the Fig. 1.

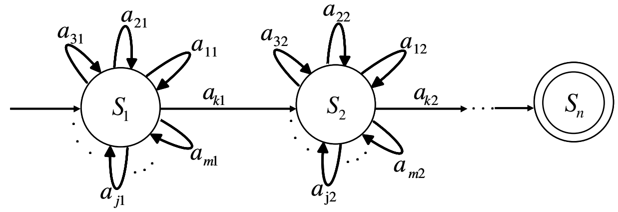

Fig. 1. The General *FSM* a_{ji} : The index j corresponds to the m-1 transitions in $\sum$ and the index i corresponds to state index, i.e., S_i, $i = 1,\ldots,n$ a_{ki} : The index k corresponds to a transition in $\sum$ and i is state index

Now we explain each of the above described three cases in detail.

1) Mapping actions to intention: The human teaches the robot his intention online. He does this by performing different actions in a sequence. The action sequence corresponds to one specific human intention. The action sequence and the corresponding scene information are received from the camera input to construct a *FSM* out of it.

This is the simplest case of online intention learning. A mapping is performed between the human actions that are performed online and the human intention by the *FSM*. The human intentions are extracted from the scene e.g., at the start of the scene, objects of similar type are placed randomly apart from each other. If the human picks one object and places the object on other similar object then the system observes the pick and place action. As the place operation is performed on the top of a similar type of object, the number of the objects decreases, observable in 2D. The extracted action sequence along with the scene information will be pick, pile and decrease in the number of objects. The already known scene information of decrease in objects corresponds to the pileup intention. The end state of the *FSM* shown in Fig. 2 is already known since the different human intentions in terms of the scene information are given. The restriction in this type of intention learning is that the image-processing system should be powerful to recognize the human actions performed by the different humans. The different persons can perform the same action with some variation.

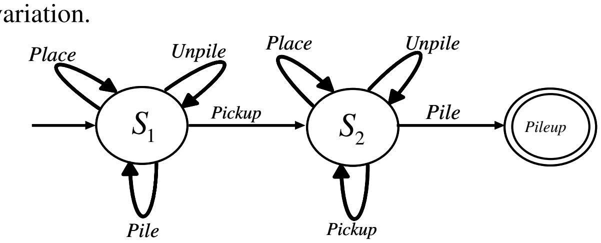

Fig. 2. *FSM* built from action sequence of pickup and pile

It is difficult for most of the image-processing systems to recognize an action that is performed differently, i.e., variation in the posture while performing the action.

2) Mapping actions to scene changes: In this type of intention learning, the input to the learning system includes the human actions along with the learning parameters.

The learning parameters are specific to a specific scene, e.g., in industry scenario the learning parameters may correspond to the assembly of two specific objects, in household scenario the learning parameters may correspond to the specific place of the specific objects, etc.

The scene information changed due to the human actions is understood through the learning parameters. The learning parameters represent the human intention concerning the observed human actions. In this case, the human intention is recognized in terms of scene information through learning parameters that concern the end state of the online constructed *FSM*. The learning parameters concerning the intention correspond to specific values of learning parameters concerning the scene. In order to explain we consider an example, i.e., there exist three objects of different types randomly in the working area and the learning parameters correspond to the distance and orientation of the objects with respect to each other. The human picks and places the objects near each other in a group. Thus the online-extracted scene information will be concerning the distance and orientation between the objects. The scene change will represent the change in the distance and orientation of the objects. The scene change, i.e., the distances and orientations between the objects is stored as the human intention. The system does not know exactly that the human intention is of grouping the objects but the system only observes the distance and orientation change and stores it.

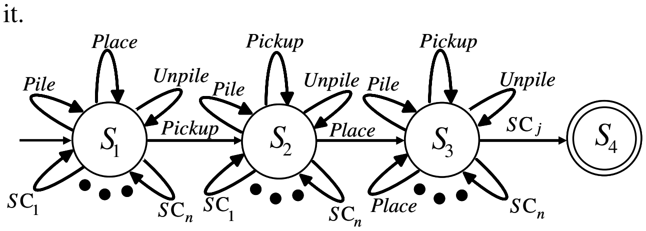

Fig. 3. *FSM* built from the action sequence of pickup and place and the scene change (SC_j)

The final state corresponds to the final change in the distance and orientation of the present objects. The robot uses that final state information to react. The *FSM* built from the action sequence (extracted out of observed human action sequence) and the final scene change is shown in the Fig. 3.

3) Mapping using the scene changes: It is very difficult to understand the human actions or human activity depending on the shape, size, orientation, etc of the human body parts. It is very difficult to model a complete set of a specific human action (perceived from all possible perspective) with the help of visual descriptors. It gets more complex if the human performs the same action but the related human has completely unexpected shape, orientation, size, etc. It is comparatively easy to recognize the objects using their features. Therefore, it is easy to recognize changes occurred in the scene, relating to the objects, due to the human actions. The human actions can be indirectly recognized from the scene changes. In this method, the learning parameters are used to infer the human actions as well as the human intentions. If the human performs a sequence of actions and each action causes a change in the scene that can be uniquely recognized by the system. Then the complete change sequence represents the human action sequence and the scene change at the end represents what the human intends to achieve. All the scene changes are used to infer the human actions and human intention using the learning parameters. Generally, it is considered that human performs actions in a sequence. Each action performed in the sequence corresponds to a scene change $s \in S$ that can be understood by learning parameters. The set $S = \{A, B, C, D, ...\psi\}$ consists of all the scene changes that can occur due to the human action and the set S is already known to the system. Then the sequence of scene changes is observed and a *FSM* is built online from the observed sequence as described earlier in Section II.

If ABCD is the online-observed sequence of scene changes then the constructed *FSM* is shown in the Fig. 4.

The last scene change D represents what the human intends to do. The scene change D is used by the robot to react in response to the recognized intention by the scene change sequence ABC. The scene changes A, B, and C are given maximum observation probabilities as compared to other scene changes at S_1, S_2 and S_3 respectively. The state transitions occur at S_1, S_2 and S_3 due to highest probable observations (scene changes), i.e., A, B and C respectively.

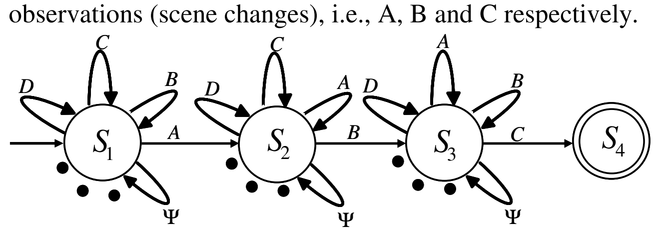

Fig. 4. *FSM* built from sequence ABCD

III. Experiments

The experiments are performed with a robotic arm of 6 degrees of freedom. The HRI workspace is shown in Fig. 5. The workspace consists of a table with objects. The buttons for Learn, Play, Pause, Stop and Reset are used to interact with the robot, shown in Fig. 6. An overhead FireWire camera is used to observe the scene, shown in Fig. 5. In order to evaluate the intention learning, different experiments were performed with three different persons (fifteen times for each phase) with respect to the three discussed cases in Section II.

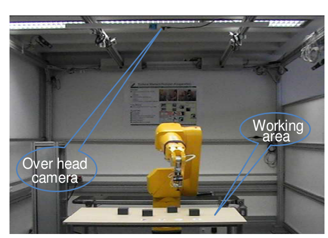

Fig 5

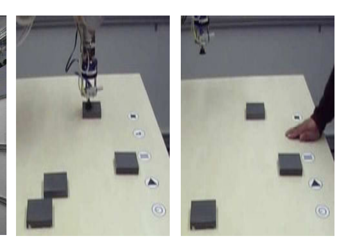

Fig 6

Fig. 5 & 6. Workspace for HRI

All the experiments have two phases, i.e., the learning phase and testing phase. In the learning phase, the human teaches the robot his intention by performing different actions in a sequence and completing the task. In the testing phase, the robot reacts by recognizing the learned intention and completes the intended task. For the first case, the performed experiments involved pilling of the objects, scattering of the piled objects, and placing the objects in a tray. In first experiment, for pilling of the objects the human starts the robot's learning phases by placing the hand on the Learn button as shown in the Fig. 6. The human performs the actions of pilling the boxes one by one. In the testing phase, the human starts the testing phase by pressing the Play button.

The human piles one box and the robot recognizes the intention of pilling and reacts by pilling the rest of the boxes. Similarly for the scattering the piled objects and placing the objects into the tray, the human first teaches the robot his intention and afterwards he tests the learned intentions. The human initiates the interaction by taking an action with respect to the intention and the robot reacts by recognizing the intention and completes the human intended task.

In the following Figs, 7, 8, 9, 10, 11, 12, the red line represents the average result of the performed experiments. The red line represents the success or failure of the performed experiments. The more the line is near to the value 1 at a point the more successful and vice versa. The successful experiments are represented by a point at the value of 1 and 0 otherwise in the following graphs.

A successful experiment means that the expected results are obtained. In case of teaching the system about a human intention, if the corresponding *FSM* is constructed then the experiment is considered successful and vice versa. In case of testing, the robot is required to react according to the human intention. If the robot reacts according to the human intention then the experiment is considered successful and vice versa.

Each point represents one result of experiments of an individual. Fluctuations in the average line represent the success and the failure due to the variance of the action postures by different humans with respect to the same action task.

The success rate is the ratio between the successful experiments with respect to the total numbers of experiments in one phase of a case. The success rate is high as the average line continues at the value 1 and vice versa. The average success rate in the learning phases is 73 % and in the testing phase the average success rate is 87 % for the Case 1.

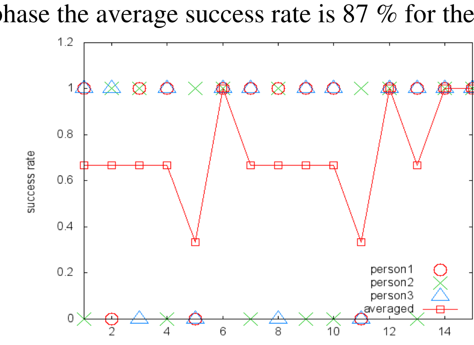

Fig. 7. Learning phase for Case 1

The fluctuation of the average line describes that mostly for each point of experiment, two persons performed successfully, as shown in the Fig. 7. The graph in Fig. 8 describes the experiment results in the testing phase of Case 1. The fluctuation in the average line of Fig. 8 is less with respect to Fig. 7. It is due to the fact that few actions are required to recognize the human intention and the robot reacts afterwards.

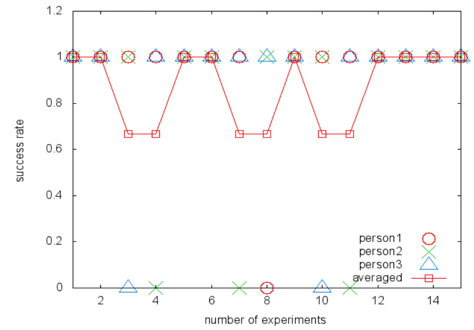

Fig. 8. Testing phase for Case 1

The reason for the difference in success rate in the testing and learning phases is due to the fact that the system has to perform more image-processing in learning phase as compared to the testing phases. Using very simple image-processing (Fourier descriptor for contour recognition and skin detection), an action performed with unexpected human body part posture is less likely to be detected. For Case 2 and 3 the performed experiments involve the placing of objects in any human intended pattern. The average line in Fig. 9 represents that the success rate is almost equal to the success rate shown in Fig. 7. The success rate of experiments is 69 % shown by the average line in Fig. 9.

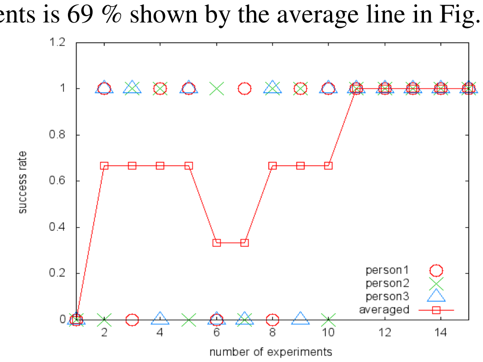

Fig. 9. Learning phase for Case 2

The success rate of experiments shown by the average line in Fig. 10 is 80 %. The difference between the success rates of experiments shown in Fig. 9 and in Fig. 10 is almost the same as in experiments shown in the Fig. 7 and in Fig. 8, due to the same reasons discussed for Case 1.

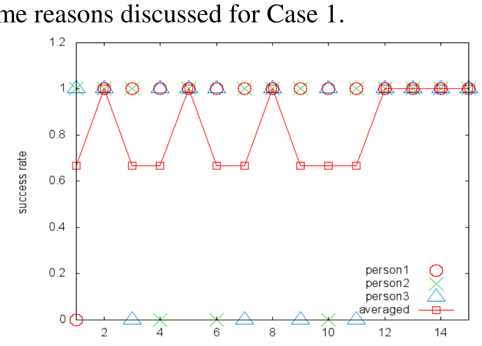

Fig. 10. Testing phase for Case 2

The success rates of experiments shown by the average lines in Fig. 11 and 12 are 100 % and 95 %. The reason of

100 % success rate is due to the fact that the action sequence was considered in terms of the scene changes performed by the human, i.e., the results of human actions are considered. It is focused in the observation that what the human has performed rather than how he has performed.

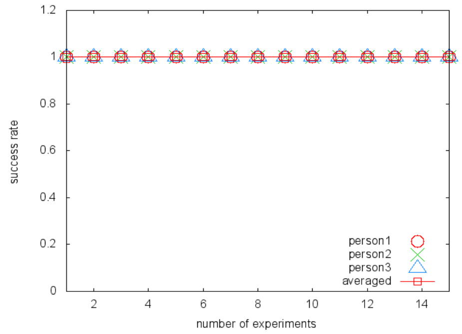

Fig. 11. Learning phase for Case 3

The ditches in the average line in Fig. 12 describe the fact that the human has performed and in response to that scene change the human intention was not recognized. Then the human made an appropriate amendment in the scene and due to that correction the intention was recognized. This fact is represented by the dotted line part in Fig. 12.

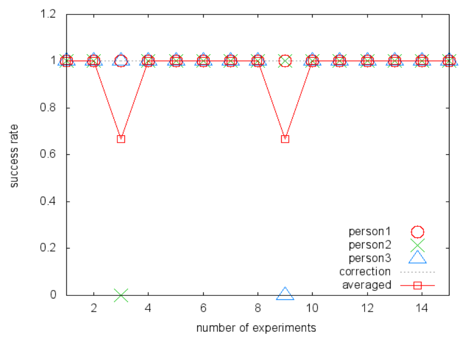

Fig. 12. Testing phase for Case 3

IV. CONCLUSION

In this paper we have discussed three cases of intention learning. The cases discussed the mapping of human intention to the corresponding observation sequence. The mechanism used for intention recognition consists of the probabilistic *FSMs* [12]. For online intention recognition a probabilistic *FSM* regarding to a specific intention is constructed online. The online intention learning contributes to the intuitive HRI capability of the robot. The experiments were performed for all the three cases of online intention learning. During the learning phase the intention is conveyed once by performing the concerned action sequence. It was observed that the Case 3 is more flexible for capturing the human actions and human intention and robust in results. The reason of comparative success for capturing human actions is the simple image-processing, in the Case 3. The results in Case 1 and Case 2 are also acceptable.

REFERENCES

[1] A. Billard and A. Hayes, G., DARMA 1999. *a connectionist architecture for control and learning.* autonomous robots, Adaptive. Behavior. 7 (1), 35-64.

[2] A. Fathi and G. Mori, *Action recognition by learning mid-level motion features*, in Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR'08), Anchorage, AK, June 2008, pp. 1–8.

[3] B. Argall and S. Schall, 1997. *Robot learning from demonstration*. In Proceedings of 14th International Conference on Machine Learning (ICML).

[4] C. Lee and Y. Xu, 1996. *Online, Interactive Learning of Gestures for Human/Robot Interface*. In IEEE Proc. International Conference on Robotics and Automation (ICRA) 2982-2987, vol.4.

[5] C. Thurau and V. Hlaváčˇ, *Pose primitive based human action recognition in videos or still images*, in Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR'08), Anchorage, AK, June 2008, pp. 1–6.

[6] F. Lv, R. Nevatia, *Single view human action recognition using key pose matching and Viterbi path searching*, in: Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR'07), Minneapolis, MN,June 2007, pp. 1–8

[7] H. Jeon, T. Kim, and J. Choi. *Ontology-based user intention recognition for proactive planning of intelligent robot behaviour*. International Conference on Multimedia and Ubiquitous Engineering, 2008.

[8] J. Yang and Y. Xu, 1993. *Hidden Markov model approach to skill learning and its application in telerobotics*. In IEEE Proc International Conference on Robotics and Automation (ICRA), 396-402.

[9] K. Mikolajczyk and H. Uemura, *Action recognition with motion appearance vocabulary forest*, in Proceedings of the Conference on Computer Vision and Pattern Recognition (CVPR'08), Anchorage, AK, June 2008, pp. 1–8

[10] K. A. Tahb. *Intention recognition of a human commanding a mobile robot*. Proceedings of the IEEE, Conference on Cybernetics and Intelligent Systems, Singapore, pages 896:1-6, 1-3 December, 2004.

[11] L, Wang and D. Sutter, *Learning and matching of dynamic shape manifolds for human action recognition*. IEEE Transactions On Image Processing (TIP) 16 (6) (2007) 1646–1661.

[12] M. Awais and D. Henrich, 2010. *Human-Robot Collaboration using Probabilistic State Machines*. In Proceedings of 19th International Workshop on Robotics in Alpe-Adria-Danube Region (RAAD).

[13] O. Weede, C. Schrempf, and U. D. Hanebeck. A Generic Model for Estimating User-Intentions in Human-Robot Cooperation, in Proceedings of the 2nd International Conference on Informatics in Control, Automation and Robotics, ICINCO 05, 2005.

[14] R. Sutton and A. Barto, 1998. *Reinforcement learning: An introduction*, The MIT Press, Cambridge, MA, London, England.

[15] R. Poppe. *A survey on vision-based human action recognition*. Image and Vision Computing, 28(6) : 976–990, June 2010.

[16] Richard et al. *Understanding Human intentions via Hidden Markov Model in Autonomous Mobile Robots*, Proceedings of ACM/IEEE international conference on Human-robot interactions, pages 367-374.

[17] S. Youn, and K. Oh. *Intention Recognition using a Graph Representation*. World Academy of Science, Engineering and Technology, 25, 2007.

[18] W. Mao, and J. Gratch. *A utility-based approach to intention recognition*. Workshop on Agent Tracking: Modeling Other Agents from Observation, 2004

[19] W. Smart and L. Kaelbling, 2002. *Effective reinforcement learning for mobile robots.* In IEEE Proc. International Conference on Robotics and Automation (ICRA), 3404-3410, vol.4.

[20] Y. Ke , R. Sukthankar, and M. Hebert, Spatio-temporal shape and flow correlation for action recognition, in Proc. Visual Surveillance Workshop, 2007, pp. 1–8